Wind Turbine Power Output Short-Term Forecast: A comparative study of data clustering techniques in a PSO-ANFIS model

Paul A. Adedeji [a]*, Stephen Akinlabi [b,c], Nkosinathi Madushele [a],

Obafemi O. Olatunji[a]

[a] *Department of Mechanical Engineering Science, University of Johannesburg, South Africa.*
[b] *Department of Mechanical and Industrial Engineering, University of Johannesburg, South Africa*
[c] *Deparment of Mechanical Engineering, Covenant University, Ota, Nigeria.*

*Corresponding Author: Email Address: pauladedeji2k5@gmail.com

Word Count: 11703

Abstract

The emergence of new sites for wind energy exploration in South Africa requires an accurate prediction of the potential power output of a typical utility-scale wind turbine in such areas. However, careful selection of data clustering technique is very essential as it has a significant impact on the accuracy of the prediction. Adaptive neurofuzzy inference system (ANFIS), both in its standalone and hybrid form has been applied in offline and online forecast in wind energy studies, though the effect of clustering techniques has not been reported despite its significance. Therefore, this study investigates the effect of the choice of clustering algorithm on the performance of a standalone ANFIS and ANFIS optimized with particle swarm optimization (PSO) technique using a synthetic wind turbine power output data of a potential site in the Eastern Cape, South Africa. In this study a wind resource map for the Eastern Cape province was developed. Also, autoregressive ANFIS models and their hybrids with PSO were developed. Each model was evaluated based on three clustering techniques (grid partitioning (GP), subtractive clustering (SC), and fuzzy c-means (FCM)). The gross wind power of the model wind turbine was estimated from the wind speed data collected from the potential site at 10minutes data resolution using Windographer software. The standalone and hybrid models were trained and tested with 70 % and 30 % of the dataset respectively. The performance of each clustering technique was compared for both standalone and PSO-ANFIS models using known statistical metrics. From our findings, ANFIS standalone model clustered with SC performed best among the standalone models with a root mean square error (RMSE) of 0.132, mean absolute percentage error (MAPE) of 30.94, a mean absolute deviation (MAD) of 0.077, relative mean bias error (rMBE) of 0.190 and variance accounted for (VAF) of 94.307. Also, PSO-ANFIS model clustered with SC technique performed the best among the three hybrid models with RMSE of 0.127, MAPE of 28.11, MAD of 0.078, rMBE of 0.190 and VAF of 94.311. The ANFIS-SC model recorded the lowest computational time of 30.23*secs* among the standalone models. However, the PSO-ANFIS-SC model recorded a computational time of 47.21*secs*. Based on our findings, a hybrid ANFIS model gives better forecast accuracy compared to the standalone model, though with a trade-off in the computational time. Since, the choice of clustering technique was observed to plays a vital role in the forecast accuracy of standalone and hybrid models, this study recommends SC technique for ANFIS modeling at both standalone and hybrid models.

Keywords: ANFIS; autoregressive model; data clustering; particle swarm optimization; wind turbine.

Nomenclature			
$\boldsymbol{P}$	Wind turbine gross output power (MW)	ρ_{site}	Air density at the proposed site (kg/m^3)
$\boldsymbol{t}$	Time	ρ_o	Nominal air density (kg/m^3)
$\boldsymbol{d_i}$	Delay ($i = 1,2, \dots 5$)	c	Number of clusters
$\boldsymbol{n}$	Sample size	P_{r_i}	Potential of cluster i being a cluster centre
$\boldsymbol{\Phi(L)y_t}$	Lag polynomial		
$\boldsymbol{p}$	Polynomial order		
$\boldsymbol{\varphi_0}$	Mean constant		
$\boldsymbol{\hat{\varphi}_i}$	Coefficient of autoregressive equation		
$\boldsymbol{\varepsilon_t}$	Error term		
$\boldsymbol{\bar{y}_i}$	Mean gross power output at ith delay.		
$\boldsymbol{k}$	ANFIS node		
$\boldsymbol{O_k^1}$	Output of adaptive node k.		
$\boldsymbol{\mu_{A_i}}$	Membership function of fuzzy set A.		
$\boldsymbol{V_{adj}}$	Adjusted wind speed		
$\boldsymbol{v_{site}}$	Wind speed of the proposed site		
$\boldsymbol{y_{adj}}$	Adjusted wind turbine output power		

1 Introduction

The need to diversify South Africa's energy mix has necessitated the development and deployment of renewable energy. Interestingly, wind energy uptake has reasonably increased in the country, thus making it one of the fastest growing renewable energy resources. Studies have shown that the country has wind resource in a harvestable amount sufficient for power generation in specific areas (Ayodele and Ogunjuyigbe, 2016; Sørensen et al., 2018; Van der Linde, 1996). However, South Africa is ranked the seventh largest coal producer on the global scale (Dunmade et al., 2019) and this has influenced her use of coal as primary source of fuel for electricity generation, though this trend is changing since the country has embraced the low-carbon economy mantra. The decision to embrace low-carbon economy is an aftermath of the Copenhagen climate change summit, where the president pledged to reduce the country's greenhouse gas emissions by 34 % in 2020 and 44 % by 2025 (Baker et al., 2014). This commitment was supported by the development of Renewable Energy Independent Power Producer Procurement Programme (REI4P), a public-private partnership programme, launched in 2011 (McEwan, 2017). Over 77 projects have been awarded to the private sector with a 20-year power purchase agreement between Eskom, the country's electricity management company, and the independent power producers (IPPs) (McEwan, 2017). Five (5) rounds of the project have been rolled out with the fifth round under development by developers. Each round consists of a nexus of renewable energy sources (wind and solar resources) for power generation. Within the past two decades, wind energy has been harnessed for power generation at a micro-grid level by several investors and this has consequentially increased with largest concentration in the Northern, Western, and Eastern Cape provinces. Based on the analysis carried out by the South African National Energy Development Institute (SANEDI) (Cape-ducluzeau and van der Westhuizen, 2015) to identify renewable energy development zones (REDZs), the Eastern Cape Province is one of the corridors identified with the abundance of wind energy (SANEDI, 2016), though generally, harvestable wind energy for power generation in South Africa is geospatially dependent.

The age-long fossil fuels have directly and indirectly engendered economic transformation, both at national and global levels. These conventional sources of energy formed the basis of the first industrial revolution in the 1800's (Nehrenheim, 2018). However, these energy sources are fast being replaced with renewable energy sources with the aim of reducing carbon emission and mitigating global warming. Unfortunately, renewable energy sources are notable for intermittency and variability, which consequentially affect their reliability. However, despite these setbacks, solar and wind energy have recorded significant successes at on-grid and off-grid levels with renewed commitments to ensure optimality in the system design and the selection of the system components (Khalili et al., 2019). The off-grid systems, which comprise local loads with distinct electrical boundaries, generation units and energy storage system often rely on a nexus of renewable energy sources to maximize energy availability (Erenoğlu et al., 2019). In contrast, on-grid systems consist of the interconnected power generation units, the transformer and the substation through which they feed into to the grid according to the specified grid code. The grid-connected system leverages the aggregation of several power generation units with the optimization of technological constraints and the efficiency of generation. In term of pricing and availability, wind energy is considered as highly naturally abundant, reasonably priced, and evenly distributed. Wind energy has also been identified as the high spot of economical and efficient energy on earth, with high potential for sustainability (Murthy and Rahi, 2017; Shoaib et al., 2019). The wind energy is harvested using wind turbine system whose generation capacity varies depending on the climatic condition of the location and the turbine power curve. Thus, a wind turbine system (WTS) can be at its peak in an hour and generate its minimum possible power at the following hour (Pelacchi and Poli, 2010). The wind turbines are capable of generating electrical energy at optimum wind conditions either during the day or at night as compared to solar photovoltaic systems (Eminoglu and Turksoy, 2019; Keeley and Ikeda, 2017). WTSs can be classified on the basis of the speed and axis of rotation. Based on speed, the WTSs can be divided into two: the constant speed and the variable speed wind turbines. Power losses (in terms of aerodynamic, electrical and mechanical losses) in these two types of WTS largely depend not only on the wind speed but also on the size, structure and type of mechanical and electrical system (Eminoglu and Turksoy, 2019). Based on axis of rotation, the WTSs can be divided into the vertical and horizontal axis wind turbines . The vertical axis wind turbines (VAWT) can receive wind at any direction, thus eliminating the yawing mechanism as observed in the horizontal axis wind turbines (HAWT). However, these types of turbines are not self-starting, which is critical to the operation of the system and their overall efficiency is lower than that of the HAWT (Mathew, 2006). The HAWTs on the other hand have many drawbacks like sensitivity to wind direction, low cut-in speed, design complexity and so on (Stathopoulos et al., 2018). The integration of active energy generated from the WTSs with the utility follows specific grid code within which these generating units can be connected to the utility (Hagh and Khalili, 2019). The problem of spatiotemporal variability and intermittency associated with renewable energy (Liu et al., 2019) have necessitated real-time forecast of resource availability from dependent variables. This helps in strategic and operational planning, in order to ensure maximum availability of energy.

Research in the field of forecasting has evolved from the use of conventional linear models such as autoregressive integrated moving average (ARIMA) to the intelligent non-linear forecasting models like the artificial neural network (ANN), support vector regression (SVR), ANFIS and so on (Adedeji et al., 2019). Linear models assume that data exhibits a linear relationship between past data values and the errors (Box et al., 2013; de Oliveira and Ludermir, 2016), however, real-world problems are non-linear. Hence, the use of non-linear models for prediction is highly essential in achieving robustness and model sensitivity to perturbation. There are several standalone non-linear forecasting techniques developed over the years, whose accuracy on new datasets is highly reliable. Examples of these are the self-organizing ANN, support vector machine (SVM), the *k*-nearest neighbour (*k*-NN), ANFIS, probabilistic neural network (PNN), the random threshold network (RTN) and so on. These techniques are not one-size-fits-all; they possess peculiar characteristics, which makes them applicable in each domain. Several non-linear forecasting models have been employed in wind energy studies. For example, singular spectrum analysis and ANFIS were used by Moreno and dos Santos Coelho, (2018) to forecast wind speed, thus decomposing the wind speed into several additive components using singular spectrum analysis and forecasting a step ahead using the ANFIS model. The study evaluated the decomposed components to ensure that influential elements from the decomposition are considered for the next phase of the model. Also, Chang et al., (2017) investigated the effectiveness of a radial basis function neural network improved with an error feedback scheme in the short-term forecast of wind speed and power of a typical wind farm near central Taiwan. Another non-linear technique which has been used to forecast wind power is the random forest technique (Lahouar and Hadj, 2017).

Soft computing techniques have helped in solving problems related to model design complexity, accuracy, computational speed, near abstraction of reality in intelligent prediction, modeling, and the control of non-linear systems (Shihabudheen and Pillai, 2018), though the efficiency and effectiveness of these techniques are highly dependent on the optimal choice of parameters for the model components (Adedeji et al., 2019). ANFIS forms one of the forecasting techniques in this domain, which have been explored across several fields due to its non-linear input-output mapping within a solution space such that local optimal value is avoided and fuzzy variables are taken into consideration. ANFIS has been applied in the fields which include; hydrological studies (Nourani and Partoviyan, 2018; Pramanik and Panda, 2009), econometrics (Najib et al., 2016), enterprise systems (Pan, 2009), molecular studies (Barati-Harooni et al., 2016), energy systems (Adedeji et al., 2018; Shabaan et al., 2018) and so on. The ANFIS technique, which follows the Takagi-Sugeno fuzzy inference system, is a five-layered network with two adaptive nodes (the first and fourth node) and the others being fixed nodes. The output of the adaptive nodes is a function of node parameters which are modified according to the learning rules in order to minimize the prescribed error (Chahkoutahi and Khashei, 2017).

The relevance of ANFIS model, either as standalone or tuned with other algorithms, in renewable energy space has been reported in recent studies. As a standalone model, Stefanakos, (2016) used the fuzzy logic and ANFIS techniques in a point-wise and field-wise forecasting of wind and wave parameters. Data of a decade long at three-hour time interval with significant wave height, wind speed, and peak wave period was used in the study. The study established that the hybrid model outperforms the standalone models of FIS and ANFIS. Similarly, Kassa et al., (2017) explored the use of standalone ANFIS on short-term prediction of wind power of an installed wind turbine in Beijing. The study compared the performance of ANFIS with backpropagation neural network (BP-NN) and its hybrid with genetic algorithm (BP-NN-GA). From their findings, ANFIS model outperformed BP-NN and BP-NN-GA with a mean absolute error of 28.39, an RMSE value of 46.06 and a mean absolute percentage error (MAPE) of 4.45, thus emphasizing the reliability and accuracy of ANFIS model. Dong and Shi, (2019) also investigated the use of ANFIS for wind power forecast in selected regions in China. The model takes as inputs the outputs from an efficiency measuring technique (data envelopment analysis-DEA) and a multi-criteria optimization technique (technique for order preference by similarity to an ideal solution- TOPSIS). An absolute error less than 1 and a root mean square error (RMSE) of 2.7527 were obtained from the test samples. The study further established key factors affecting China's exploration of wind energy, using a regression model. Also, ANFIS optimized with other algorithms have been investigated in the literature. Pousinho et al., (2011) optimized ANFIS with particle swarm optimization (PSO) to predict wind power. In the study, wind resource was divided based on the four seasons experienced in Portugal and the accuracy of the model for the four seasons were commendable. Asides in wind resource forecast, the hybrid ANFIS models have also been explored in predicting other renewable energy resources. For example, Khosravi et al., (2018) investigated the performance of several artificial intelligence techniques in estimating daily global solar radiation. The study compared intelligent forecasting techniques and the conventional methods. In the study, group method of data handling (GMDH) neural network, multilayer feedforward neural network (MLFFNN), ANN and ANFIS hybrids with PSO, genetic algorithm (GA), and ant colony optimization (ACO) was investigated. Of all the models in the study, the GMDH neural network outperformed the other models with a root mean square error of 0.2466 kWh/m^2. However, among the hybrid ANFIS models used, the ANFIS hybrid with PSO recorded the least root mean square error of 0.4412 kWh/m^2. In all these studies, despite the significant effectiveness demonstrated by PSO-ANFIS model, the effect of clustering technique was not investigated.

In recent times, the significant technological developments in renewable energy harvesting technologies is now concomitant with an avalanche of data generated from sensor technologies of these systems towards improved system efficiency, thus making data clustering to be of high importance. Most real-time systems are built with data logging capabilities with a three-dimensional data definition: the data velocity, complexity, and size (Tang and Fong, 2018; Torrecilla and Romo, 2018). This tripartite nature of the data has therefore made its analysis, retrieval, and processing both challenging and time-consuming (Sassi Hidri et al., 2018). Data clustering has recently been used in the data analysis problem wherein the clustering process compacts the data while retaining the data information. Clustering is an essential process in ANFIS modeling. Clustering techniques are used to identify the group where an observation belongs with a balance between homogeneity within the clusters and heterogeneity between the clusters (Shamshirband et al., 2016; Sheikh et al., 2008). In reference to South Africa, the development of allocated wind sites for the round five is ongoing in Eastern Cape Province. The next bidding window is on its way and more wind farms will be sited in the area, thus an effective intelligent model, which effectively forecasts the expected gross output power and better clusters the data is vital to optimal plant operation and strategic decision-making.

Against this background, the motivation of this study is to bridge the knowledge gap by investigating the significance of the clustering technique in both standalone ANFIS and optimized ANFIS models on a wind turbine output data of a potential site prior to the wind turbine installation. The gross and not the net power output of the proposed wind turbine is of interest in this study due to variability in losses. Most feasibility studies often assume a loss factor to calculate the net power output of the turbine. However, in the reality, the loss factor is a geospatial variant. The selection of the PSO-ANFIS hybrid model was due to its efficiency and robustness in previous studies in forecasting. The use of PSO in ANFIS model resolves one of the major problems called parameter tuning, often associated with black box models. Asides optimality in the model parameters, the type of clustering technique in the hybrid model is hypothesized to plays an important role in ensuring model effectiveness and efficiency. This study therefore (i) develops a resource map for Eastern Cape Province and identified an area rich in wind energy, (ii) develops three autoregressive standalone ANFIS models (ANFIS-GP, ANFIS-SC, and ANFIS-FCM) using three different clustering techniques: the grid partitioning (GP), the subtractive clustering(SC), and the fuzzy c-means clustering(FCM), (iii) develops PSO-ANFIS models with three clustering techniques (PSO-ANFIS-GP, PSO-ANFIS-SC, and PSO-ANFIS-FCM) to forecast gross power output of a wind turbine (iv) evaluates the relative performance of the standalone and hybrid ANFIS models using relevant statistical metrics and also tests the hypothesis that the choice of clustering technique significantly affects the model effectiveness and efficiency. Based on the standalone and hybrid models, this study therefore recommends the best clustering technique in ANFIS modeling among the three clustering techniques considered.

The rest of the study is structured as follows: section 2 discusses the mathematical tools used in this study, thus giving a background knowledge of the concepts used in this study, ranging from data clustering techniques, autoregressive and ANFIS models. The method of data collection and the wind resource mapping of the study area was also discussed. Section 3 presents the results of the standalone and hybrid models on the case study, while section 4 concludes the study.

2. Mathematical Tools

2.1 Data Clustering

The advent of internet of things (IoT) have revolutionized the data space with an increasing competition in both manufacturing and service industries. Big data has helped to unravel the cause behind events explained with traditional analytic techniques for improved decision making both at strategic and operational level (Ghasemaghaei et al., 2018; Ghasemaghaei and Calic, 2019; Horita et al., 2017). Clustering techniques have formed significant part in data mining algorithms. Clustering unveils the intrinsic relationships that exist between a set of unlabelled data, thus ensuring a high inter-similarity within same cluster and inter-similarity across clusters (Tang and Fong, 2018). In clustering techniques, a dataset Y is partitioned into a set of C_i clusters $(\subseteq i = 1,2, \dots c)$ often performed in an unsupervised manner (Hernández et al., 2012).

Clustering techniques used in data mining algorithms can be categorized into four as shown in Figure 1 and discussed briefly follows:

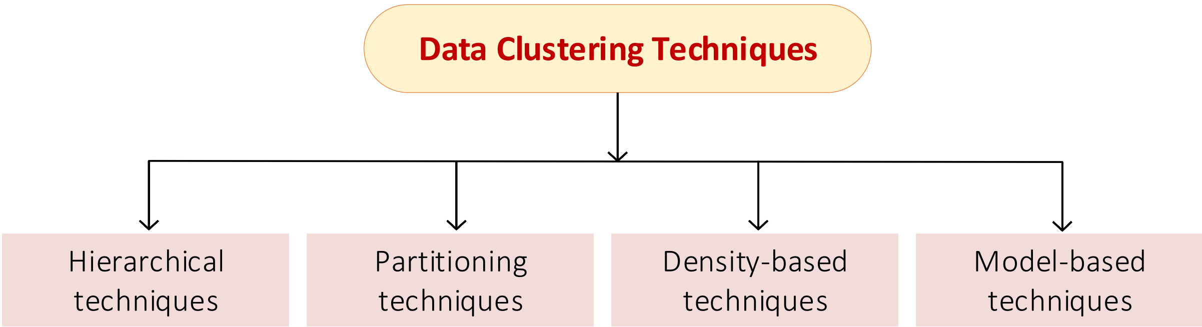

Figure 1. Categories of data clustering techniques.

a. *The hierarchical techniques:* the operation of these techniques is based on a measure of distance between objects or features with the premise that features are more related to the near features than the far ones. Hierarchical techniques decompose a dataset Y, representing it using a dendogram, a tree that iteratively divides the dataset into smaller subsets till each subset contains only one observation. A bottom-up approach (agglomerative approach), merging the clusters at each step or a top-down approach (divisive approach), diving the clusters at each step relative to the leaf orientation can be used (Ester et al., 1996; Grün, 2016). In hierarchical clustering, the number of clusters are not determined in advance, thus eliminating the challenges of local minima and initialization (Kuwil et al., 2014).

b. *The partitioning techniques:* This technique partitions the dataset Y consisting of n observations into c clusters proceeding basically in a two-step manner. First, a k representative which minimizes an objective function is determined and second, each observation is assigned to a cluster with its representative with the highest proximity to the observation in question. The partition is synonymous to a Voronoi diagram where each Voronoi cell contains each cluster thereby forming a convex shape, which is highly restrictive (Awan and Bae, 2014; Ester et al., 1996; Nayak et al., 2013). Basically, partition clustering techniques are categorized into two: hard (crisp) and the soft (fuzzy) clustering. While an observation can belong to one and only one cluster in hard clustering, the observation can belong to more than one cluster to a certain degree in soft clustering. Partitioning clustering techniques are considered as dynamic with mobility of observations from one cluster to another (Kuwil et al., 2014). One of the most common algorithms in this space is the k-means algorithm. A modified form of this algorithm is the fuzzy c-means clustering, which is an improvement on the k-means technique.

c. *The density-based techniques:* The density-based clustering technique was introduced with the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) by Martin et al. (Ester et al., 1996). In this technique, each cluster point in its neighbourhood according to a given radius contains several points or observations whose density exceeds a threshold either in a 2-dimensional or 3-dimensional space. A multi-resolution grid is used as a data structure to establish clusters. One of the advantages of density-based clustering techniques is that it does not require pre-specifications (Kuwil et al., 2014). It also performs well even when the data is highly noisy. However, its efficiency is reduced in data with high dimensionality. This technique is notable for speed and the speed is not a function of the number of observations in the dataset, though this is a function of the amount of cells in the solution space (Kuwil et al., 2014; Verma et al., 2012).

d. *Model-based techniques:* these category of clustering technique is also an unsupervised learning model whose foundation is in the probability theory (Csereklyei et al., 2017). Model-based clustering techniques aim at optimizing the fit between a dataset and specific mathematical models with an assumption that the data originates from a mix of different probability distributions (Tang and Fong, 2018). Model-based techniques can estimate the number of classes present in a dataset as well as their parameters (Melnykov and Zhu, 2018). Also, its mode of operation is fuzzy and not crispy, hence a form of soft clustering technique.

However, model-based techniques accrue a high computational time especially when a large dataset is involved. Also, the fundamental models on which the new model is built must be specified. A common example of this technique is the Expectation Maximization (EM) technique, often used in estimating maximum likelihood of parameters and ensuring the convergence of the likelihood function (Andrews and McNicholas, 2013; Sammaknejad et al., 2019).

2.2 Autoregressive Model

The conventional ANFIS model follows an input-output paradigm. However, a univariate time series data of the gross power output was used in this study. The autoregressive (AR) model was selected in this study due to its simplicity parameter estimation and explaining the current value of a series by a linear combination of the past values with a random error in the series. Unlike the moving average (MA) technique whose parameter estimation is not simple and the autoregressive moving average (ARMA) model associated with parameter redundancy and stationarity problems, the AR model suffers less from these (Dinda and O'Hallaron., 2000; Endo and Randall, 2007). To predict the gross energy output of the selected wind turbine, the model was structured such that the next gross power output $P(t+1)$ minute along the trend can be predicted using lagged time vectors with a delay $d_i (i = 1, \dots 5)$. Model inputs were the time series data with the delays, while the output forms the actual gross power output from the wind turbine. Given a time series $P_1, P_2, \dots P_n$ of a sample size n, the future values of the series are predicted from the past values within the series according to:

$$\Phi(L)P_t = \varphi_0 + \varepsilon_t \qquad \varepsilon_t \sim NID[0, \sigma_\varepsilon^2] \qquad (1)$$

where $\Phi(L)P_t = 1 - \varphi_1 L - \cdots \varphi_p L^p$ gives that the lag-polynomial with model order p and φ_0 is a series mean constant. In autoregressive models, the stationarity condition must be satisfied relative to the restriction that ε_t is independent of $P_{t-1},\ P_{t-2}, \dots$ and that $\sigma_\varepsilon^2 > 0$ (Hillier, 2001; Wang et al., 2014). In that case, a stationary solution exists if and only if the autoregressive characteristic equation has the absolute value of its root exceeding unity.

$$P(t) = f\big(P(t-1), \dots P(t-d)\big) \qquad (2)$$

From the least square method, the autoregressive model parameters were calculated using:

$$\varphi_0 = \bar{y}_0 - \sum_{i=1}^{p} \varphi_i \bar{P}_i, \qquad (3)$$

$$(\varphi_1, \varphi_2, \dots, \varphi_p)^T = \left(L_{\eta\eta}\right)_{p\times p}^{-1} \left(L_\eta\right)_{p\times 1} \qquad (4)$$

where the observation mean, $\bar{P}_i,\quad i = 0,1, \dots, n$ can be calculated using:

$$\bar{P}_i = \frac{1}{n-p} \sum_{t=1+p}^{n} P_{t-p} \qquad i = 0,1, \dots p \qquad (5)$$

and the $L_{\eta\eta} = (S_{ij})_{p\times p}$ is a matrix in the pth order, however, $L_\eta = (S_1, S_2, \dots, S_p)^T$ is a column vector in the pth order, whose constituting elements can be determined using:

$$S_{ij} = \sum_{t=p+1}^{n} (P_{t-i} - \bar{P}_i)(P_{t-j} - \bar{P}_j) \qquad i,j = 1,2, \dots, p \qquad (6)$$

$$S_i = \sum_{t=p+1}^{n} (P_t - \bar{P}_0)(P_{t-i} - \bar{P}_i) \qquad i = 1,2, \dots, p \qquad (7)$$

Estimating the coefficient of the autoregressive characteristic equation (1), $\hat{\varphi}_0, \hat{\varphi}_1, \hat{\varphi}_2, \dots, \hat{\varphi}_p$, the autoregressive prediction model equation then becomes:

$$\hat{y}_{n+l|n} = \hat{\varphi}_0 + \sum_{i=1}^{p} \hat{\varphi}_i \, y_{n+l-i|n} \tag{8}$$

such that $\hat{y}_{n+l|n}$ is the l −step-ahead prediction at a time $n+l$.

2.3 Adaptive Neuro-fuzzy Inference System (ANFIS) model

Adaptive Neuro-fuzzy inference system is a multi-layer feedforward network, which combines the neural network and fuzzy logic modeling capabilities in an adaptive manner to imitate an expert decision-making process (Fattahi, 2016). The architectural framework of ANFIS consists of five layers vis-à-vis the fuzzy, product, normalization, defuzzification, and the summation layer in the order of layers from 1 to 5 as shown in Figure 2 (Adedeji et al., 2018; Jang, 1993; Karaboga and Kaya, 2018). The ANFIS modeling technique is a variant of the Takagi-Sugeno fuzzy system, which has two components: the antecedent and the consequence.

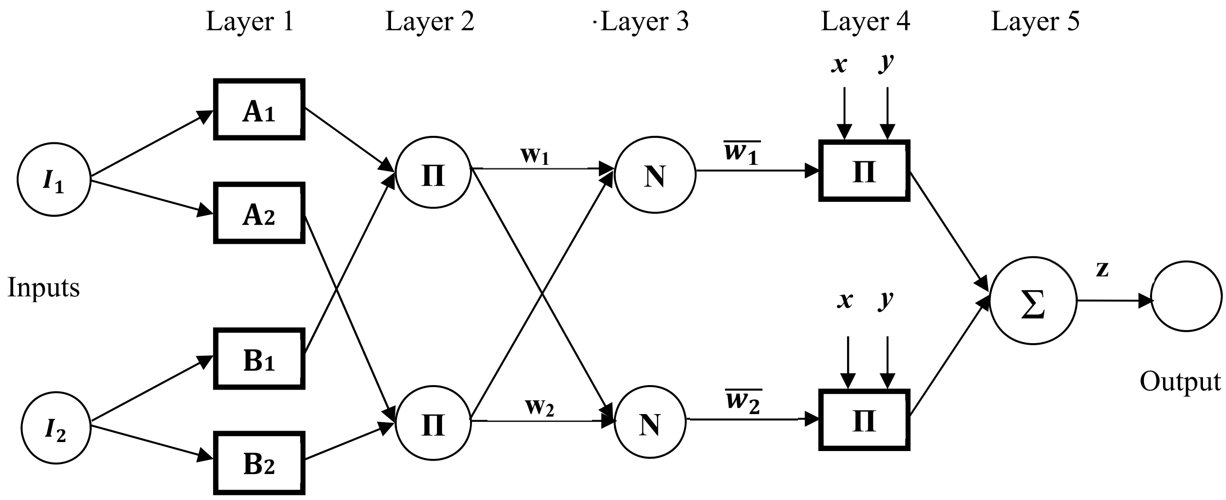

Figure 2. ANFIS model architecture showing the five layers

This technique uses hybrid learning rule comprising of backpropagation gradient descent and least square methods for model premise and consequent parameter optimization. Shown in Figure 2 is the conventional model architecture of an ANFIS network while Figure 3 shows the integrated framework of the model with three clustering techniques.

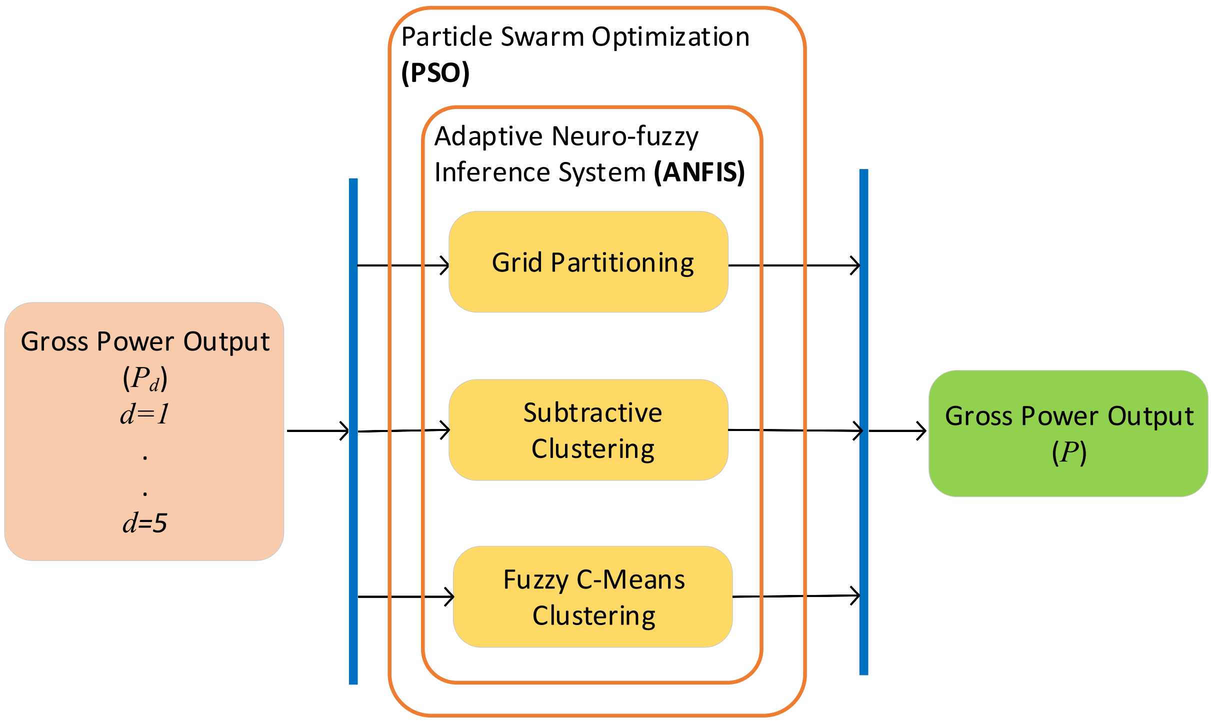

Figure 3. Standalone and hybrid ANFIS model framework with the three clustering techniques. Each clustering technique was considered independently, resulting in six models in all.

In Figure 1, layer 1 consists of fuzzy membership functions with output functions for each node represented as:

$$O_k^1 = \mu_{A_k}(x)\,, k = 1, 2 \tag{9}$$

$$O_k^1 = \mu_{B_k}(y)\,, k = 1, 2 \tag{10}$$

Layer 2 computes the firing strength of a rule using multiplicative operator as:

$$O_k^2 = w_k = \mu_{A_k}(x)\,.\,\mu_{B_k}(y) \quad , k = 1, 2 \tag{11}$$

Layer 3 normalizes the firing strength at the kth node of the structure using the ratio between the firing strength in the kth node and the sum of all firing strengths from all the rules (Eqn. 12). Nodes in this layer are non-adaptive.

$$O_k^3 = \overline{w_\iota} = \frac{w_k}{w_1 + w_2} \qquad k = 1, 2 \tag{12}$$

Layer 4 uses a nodal function to calculate the effect of kth rule towards the output of the model using:

$$O_k^4 = \overline{w_\iota}(\,p_k x + q_k y + r_k) = \overline{w_\iota} z_k \tag{13}$$

where $p_k, q_k,\ and\ r_k$ are parameter sets of the node and $\overline{w_\iota}$ is the normalized firing strength of the third (3) layer.

Layer 5 has a single non-adaptive node, which calculates the overall output of the ANFIS model using a summation operation (Suparta and Alhasa, 2016):

$$O_k^5 = \sum_k \overline{w_\iota} z_k = \frac{\sum_k w_k z_k}{\sum_k w_k} \tag{14}$$

2.4 Data Collection

The wind speed data used in this study is the Wind Atlas of South Africa (WASA 2) dataset collected with cup anemometers mounted at 60m over a period of 6months. The geographical location of mounting is the Rhodes located in Eastern Cape, South Africa. The meteorological mast from where the data was collected is located at 28.07351°E, 30.81436°S as shown with a placemark in Figure 4. The location offers a high potential for wind energy generation owing to its associated high wind speed. The measuring instrument logs climatological data at a data resolution of 10 minutes, which can be used for further analysis. The wind energy profile of the proposed site was developed using ArcGIS 10.4 with a resolution of 30 x 30m. Figure 4 shows areas in the Eastern Cape province with a wind speed of 5m/s and above. The area is highly viable for wind energy generation with prospect of wind speed up to 19m/s.

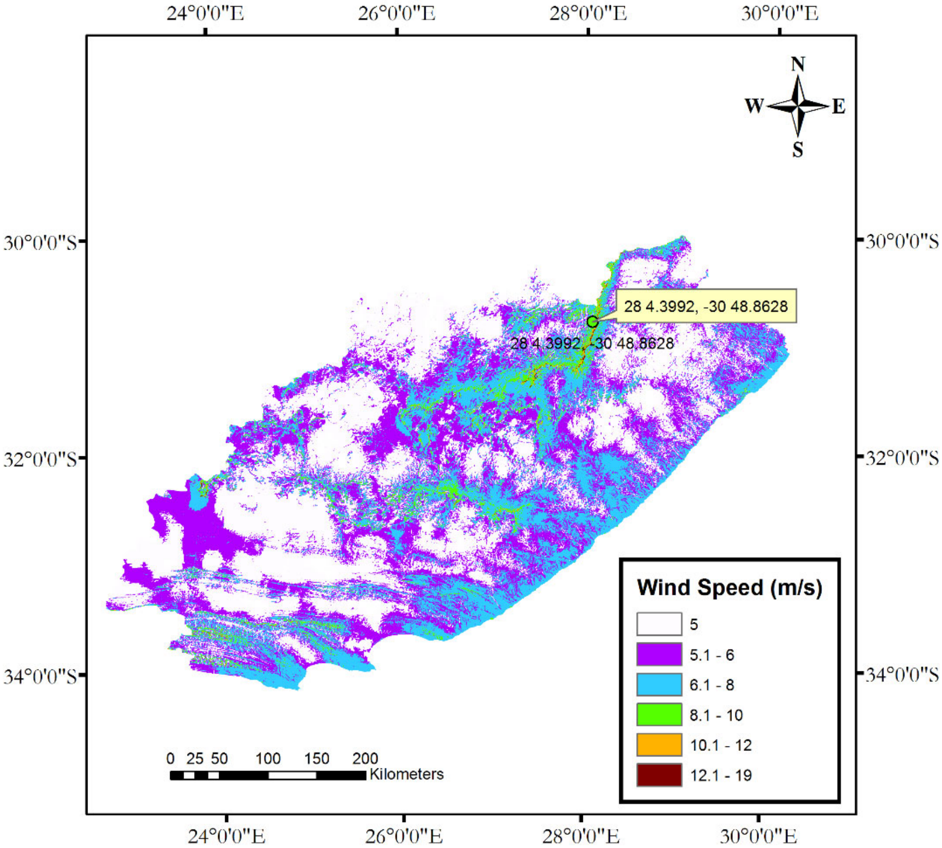

Figure 4. Wind speed distribution of Eastern Cape Province, South Africa. The location with a placemark is where the data was collected.

Short term forecast in a time step of 10minutes was performed on the gross power output of a typical wind turbine. There are several wind turbine manufacturers with each product different in effectiveness, efficiency, and application. For this study, a utility scale wind turbine was chosen without preferences or skewness to manufactures. The characteristics of the turbine are as presented in Table 1.

Table 1. Characteristics of the selected turbine

Features	AW 70/1500
Rated Power (kW)	1,500
Cut-in wind speed (ms^{-1})	4.0
Rated wind speed (ms^{-1})	11.6
Cut-out wind speed (ms^{-1})	25.0
Rotor Diameter (m)	70.0
Swept Area (m^2)	3,848
Power density (W/m^2)	389.8

Hub Height (m)	60/80
Onshore	Yes

2.5 Gross mean power output

Wind energy is harvested by converting the kinetic energy in a wind stream to mechanical energy and then to electrical energy. The gross mean power output of the turbine presents the total power expected from the turbine. This depends basically on four factors: the power curve of the wind turbine, the air density, the wind speed at the hub height, and the blade swept area (Hernández-Escobedo et al., 2014; Lee et al., 2012). The net power output can be estimated from the gross power output using the loss factor. The power curve of the turbine model considered in this study is shown in Figure 4. Neglecting losses such as wakes, turbine downtime, electrical losses and so on, the gross mean power output can be determined using the time series datasets of wind speed and air density collected at specific hub height. The power output was calculated at the adjusted wind speed (Hernández-Escobedo et al., 2014). However, the adjusted wind speed was obtained using:

$$V_{adj} = v_{site} \left(\frac{\rho_{site}}{\rho_o} \right)^{\frac{1}{3}} \qquad (15)$$

where ρ_{site} represents the air density of the proposed site (in kg/m^3) and ρ_o is the nominal air density (in kg/m^3) for which the power curve is described. For the utility scale wind turbine, the adjusted power output of the wind turbine is estimated using:

$$P_{adj} = P \left(\frac{\rho_{site}}{\rho_o} \right) \qquad (16)$$

where P is the turbine output power (in MW) for a specified speed at nominal air density. The wind speed varies at different time intervals across the period of measurement. This apparently makes the gross power output of the turbine to vary periodically.

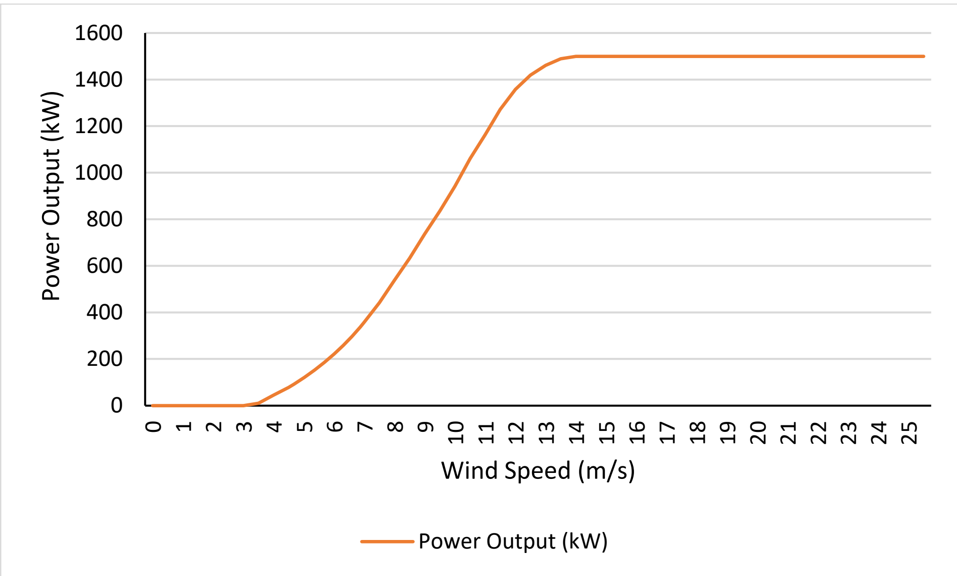

Figure 5. The power curve of the model turbine

Shown in Figure 5 is the power curve of the selected wind turbine. This illustrates the cut-in speed, the cut-out speed, the rated output speed, and the rated output power as presented in Table 1. The gross wind power for the selected turbine was estimated using the professional edition of Windographer 4.1.14 software.

The six-month dataset was divided into training and testing data in the ratio of 70 % and 30 % respectively. Three clustering techniques were investigated on the data and their results compared.

These are grid partitioning (GP), subtractive clustering (SC), and fuzzy c-means clustering (FCM) which are further discussed in subsection 2.6.

2.6 Clustering techniques

Determining membership function for each input is essential in fuzzy processes. Data clustering is one of the essential processes of the ANFIS modeling as it groups observed data into similar fuzzy clusters for the purpose of assigning a fuzzy membership function. It is used to establish representative behaviour of a multi-dimensional non-linear system comprising a large time series dataset (Çakit and Karwowski, 2015; Zare and Koch, 2018). Data clustering is employed in image segmentation (Dhanachandra et al., 2015; Gogoi and Sarma, 2012), pattern recognition (Rezaei and Zarandi, 2011), fault diagnosis (Zuo et al., 2010), and so on. Details of these clustering techniques are discussed as follow;

2.6.1 Grid Partitioning

Fuzzy partitioning techniques are useful in obtaining fuzzy members from a dataset. There are three common fuzzy partitioning techniques used in fuzzy modeling. These include grid, tree, and scatter partitioning. Unlike the other two types, the GP technique uses similar membership functions on the input space to generate equal partitions within the symmetric membership function (Galindo, 2008). It divides the input space into different fuzzy slices with each associated with a membership function. Fuzzy rules can be generated from the input-output dataset used for model training. The model performance is highly dependent on the grid definition as better performance is obtained from a finer grid. In the process, the antecedent parameters are optimized as the grid is created (Ramón and Dopico, 2011). One associated drawback of this technique is an exponential explosion of the number of membership functions as the input variables increase. This setback is called curse of dimensionality (Vasileva-Stojanovska et al., 2015). In this study, the Gaussian membership function is selected and its parameters were calculated as follows (Narayanan et al., 2015) and the GP model parameters are as presented in Table 2.

Data Matrix: *P*

Number of clusters: c

Membership function type: Gaussian

Model input: $\{P, c\}$

Model Output: $\{P, c\}$ for the Gaussian membership function (mf) F_k $(k = 1, \dots, c_j)$

start

for each gross power output in *P*

mf_n(j) = initialise the number of mfs for j

range(j,1) = $Min(P_j)$

range(j,2) = $Max(P_j)$

sigma= $[range(j,2) - range(j,1)/(2/(mf\_n(j)\ ) - 1)]/\sqrt{2 \times \log{(2)}}$

S= sigma$\times$ $ones(mf_{n(j)}, 1)$

$c(1{:}\,mf\_n(j)) = linspace(range(j,1), range(j,2), mf_{n(j)})$

end

end

Table 2. ANFIS parameters for ANFIS-GP model

ANFIS Parameter	Value
Number of Nodes	92
No of Nonlinear Parameters	192
Total No of Parameters	212
Training Data Pairs	12,197
Testing Data Pairs	5,227
Clustering Parameters	
Input membership function	Gaussian
Output membership function	Linear

2.6.2 Subtractive clustering technique

The subtractive clustering technique identifies a data point with the highest potential as a cluster centre. This is based on the distance function. The technique estimates the prospect of a data point being a cluster centre using:

$$P_{r\_i} = \sum_{j=}^{n} e^{-\alpha \|P^i - P^j\|^2} \tag{17}$$

where $\alpha = \frac{\gamma}{r_a^2}$, P_{r_i} represents the potential of the *ith* data point being a cluster centre, *n* is total the number of data points, P^i and P^j are data vectors within the observations including inputs and output, γ is a positive constant, r_a is a positive constant which defines radius of the hypercluster in the observation space. The emergence of a new centre cluster attracts a penalty for clusters within the neighbourhood of the new cluster. The potential for new clusters is calculated by subtraction using:

$$P_{r\_i} = P_{r\_i} - P_{r\_k}{}^{*} \zeta \tag{18}$$

where $\zeta = e^{-\beta \|P^i - c^k\|^2}$; $\beta = \frac{4}{r_b^2}$; $r_b = \eta * r_a$

$P_{r_k}{}^{*}$represents the potential of *kth* cluster centre, x^i is data point subtracted, c^k is the *kth* cluster centre, η is the squash factor (>1). It is ensured that the constant $r_b > r_a$ to prevent closely spaced cluster centres. There are basically four parameters, which influence the number of rules and error performance measures in subtractive clustering technique. These are the accept ratio, the reject ratio, the cluster radius, and the squash factor. One of the main advantages of this technique is its ability to process many input observations (Tien Bui et al., 2012), which is the case in this study. More details on the technique can be obtained from (Demirli et al., 2003). In this study, the following values were chosen for these parameters as presented in Table 3.

Table 3. Model parameters for ANFIS-SC model

ANFIS Parameter	Value
Number of Nodes	44
No of linear parameters	18
No of Nonlinear Parameters	30
Total no of Parameters	48
Training Data Pairs	12, 197
Test Data Pairs	5,227
Clustering Parameters	
Computing radius	0.55
Epochs	100
Initial step size	0.01
Step size decrease rate	0.90
Step size increase rate	1.10

2.6.3 *Fuzzy c-means clustering*

The FCM clustering method is a fuzzified version of the k-means algorithm. The technique originates from conventional Euclidean distance function that includes hyper spherical clusters (Küçükdeniz et al., 2012). The algorithm starts with an initial guess of a cluster centre. This technique gives membership degree to each data and guides the data centres through by continuously updating the centres and the membership of each data point unlike the hard clustering techniques where an observation can only belong to one and only one cluster (Barak and Sadegh, 2016; Rezakazemi et al., 2017; Ross, 2004; Shamshirband et al., 2016). In FCM, a goal function, which is the distance of each data point to the data centre weighted by the degree of membership of the data point is minimized using:

$$J_m(U,v) = \sum_{i=1}^{N}\sum_{j=1}^{c} U_{ij}^{m} \left\|P_i - v_j\right\|_A^2, \qquad 1 \le m \le \infty \tag{19}$$

where v_j = the centre of cluster j

c = number of clusters | $2 \le c < n$

P_i= vector data of observations of power output

m = weighting exponent

A = positive definite $(n \times n)$ weight matrix

$\|\ \ \|$ = n −dimensional Euclidean space wherein sample data belong.

The FCM technique was computed as follows:

a. Initialize randomly a μ^o membership matrix.
b. Calculate the prototype vectors, v_i such that

$$v_i = \frac{\sum_{j=1}^{n} \mu_{ij}{}^{m} y_j}{\sum_{j=1}^{n} \mu_{ij}{}^{m}}\ ; 1 \le i \le c$$

c. Evaluate the membership values of observations using:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{kj}}\right)^{\frac{2}{m-1}}} \tag{20}$$

such that $1 \le i \le c \quad , \ 1 \le j \le n$

d. Compare $\mu^{(t+1)}$ with $\mu^{(t)}$, where t= number of iterations.
e. If $\left\|\mu^{(t+1)} - \mu^{(t)}\right\| < \varepsilon$ stop, else, return to step 2, where ε is the convergence value.

The model parameters used in this study is as presented in Table 4.

Table 4. Model parameters for ANFIS-FCM model

ANFIS Parameter	Value
Number of Nodes	44
No of linear parameters	18
No of Nonlinear Parameters	30
Total no of Parameters	48
Training Data Pairs	12,197
Test Data Pairs	5,227
Clustering Parameters	
Number of clusters	10
Partitioning matrix exponent	2
Maximum number of iterations	100

Minimum Improvement	1e-5

2.7 PSO- ANFIS hybrid multi-cluster model

The PSO algorithm is hails from its strong relationship with artificial life but more closely related to the swarm methodology. In its mode of operation, the PSO is similar to the genetic algorithm (GA). However, it does not suffer the many difficulties as associated with GA where a perturbation in genetic population results into a destruction of the previous knowledge of the problem except in the case of elitism. In contrast to this, PSO retains the knowledge of good solutions within the particles (Eberhart and Kennedy, 2002). The algorithm is based on five principles of swarm intelligence as specified by Millonas (Millonas, 1994). They are the proximity, quality, diverse response, stability, and adaptability principles, which enhance its performance compared to GA.

In this study, PSO optimization model tunes the parameters of the adaptive layers (first and fourth layers) of the three standalone ANFIS models (ANFIS-GP, ANFIS-SC, and ANFIS-FCM) thus avoiding local minima. A vector comprising the antecedent and consequent parameters of the ANFIS model are optimized by the PSO algorithm. Initialization into random values of the variables of all particles in the swarm in performed with the error criterion as the fitness function. Upon initialization, the PSO algorithm updates all particle positions and velocities accordingly to set rules over stipulated number of generations until convergence is achieved. In each iteration, the values of the antecedent and the consequence parameters of the ANFIS model are considered such that a consequential update of the personal and global best experiences is performed. When the cost function of any particle is lower than the $Pbest$ obtained since the inception of the iteration, the present cost function is set as the new $Pbest$. Similarly, the cost function of the best particle is compared with the previously achieved costs. If the cost function at the present iteration is better, the present cost is made the new $Gbest$. The iterative process is repeated until specified convergence criterion is satisfied. The results of the PSO are optimized values for the antecedent and the consequent of the ANFIS model, which are assigned accordingly. The procedure for the hybrid model is described as follows:

Step 1: Create a time series data of the model input

Step 2: Generate initial FIS structure using the three different clustering techniques in the ANFIS standalone (GP, SC, and FCM)

Step 3: Generate initial swarm as follows:

(i) Generate random population size (Particles), P of length Var_Size each and positions $p_{k,l} \in (P_{min}, P_{max})$ such that $k = 1, 2, 3, \ldots, Pop_{Size}; l = 1,2,3, \ldots, Var\_Size$
(ii) Initialize the velocity of each particle ($Inital\_Vel = 0$).
(iii) Initialize the best cost at $Gbest$ ($Inital\_BestCost = \infty$).

Step 4: Create next generation of particle with updated position, velocity, and inertia weight according to the equations (21), (22), and (23) respectively (Semero et al., 2018).

$$x_i(t) = x_i(t-1) + v_i(t) \quad (21)$$

$$V_i(t) = \omega v_i(t-1) + \rho_1(Pbest - x_i(t-1) + \rho_2(Gbest - x_i(t-1) \quad (22)$$

$$\omega = \omega_{damp} \times \omega \quad (23)$$

such that the random variables $\rho_1 = C_1 r_1$ and $\rho_2 = C_2 r_2$; $r_1, r_2 \sim U(0,1)$, C_1 *and* C_2 are positive cognitive and social acceleration coefficients respectively of which stability of the algorithm is ensured when $C_1 + C_2 \leq 4$ (Kennedy, 1998), ω is the weight inertia, and ω_{damp} is the inertia weight damping ratio.

Step 5: Assign optimized particle parameters to the ANFIS structure.

Step 6: Evaluate the cost of each particle using a conditional statement, updating the $Pbest$ and $Gbest$ values, such that:

$$If\ Cost_i\ |_{it} < Cbest_p$$

$$P_i\ |_{it} = Pbest$$

$$C_i\ |_{it} = Cbest_p$$

$$If\ Cbest_p < Cbest_G$$

$$Cbest_p = Cbest_G$$

$$Pbest = Gbest$$

$$end$$

$$end$$

Step 7: Check if stopping criterion of maximum iteration is satisfied. If not satisfied, the algorithm returns to step 4, else proceed to step 8.

Step 8: Perform a short-term forecast of the gross power output of the wind turbine.

Step 9: Perform statistical performance evaluation on the forecast.

Step 10: Plot a comparison between actual turbine output and PSO-ANFIS forecast.

Step 11: Terminate the program.

Table 5. Model parameters for the PSO algorithm

Model Parameter	Value
Initial Swarm Size	20
Maximum Iteration	600
Social acceleration coefficient ($\boldsymbol{C_2}$)	2
Cognitive Acceleration Coefficient ($\boldsymbol{C_1}$)	2
Inertia Weight, $\boldsymbol{\omega}$	0.5
Inertia weight damping ratio, $\boldsymbol{\omega_{damp}}$	0.8

The PSO optimization control parameters used for the three PSO-ANFIS models are presented in Table 5. These parameters were chosen based on literature (Engelbrecht et al., 2019). This procedure was repeated for PSO-ANFIS-GP, PSO-ANFIS-SC, and PSO-ANFIS-FCM models. A flow diagram of the model is as shown in Figure 6.

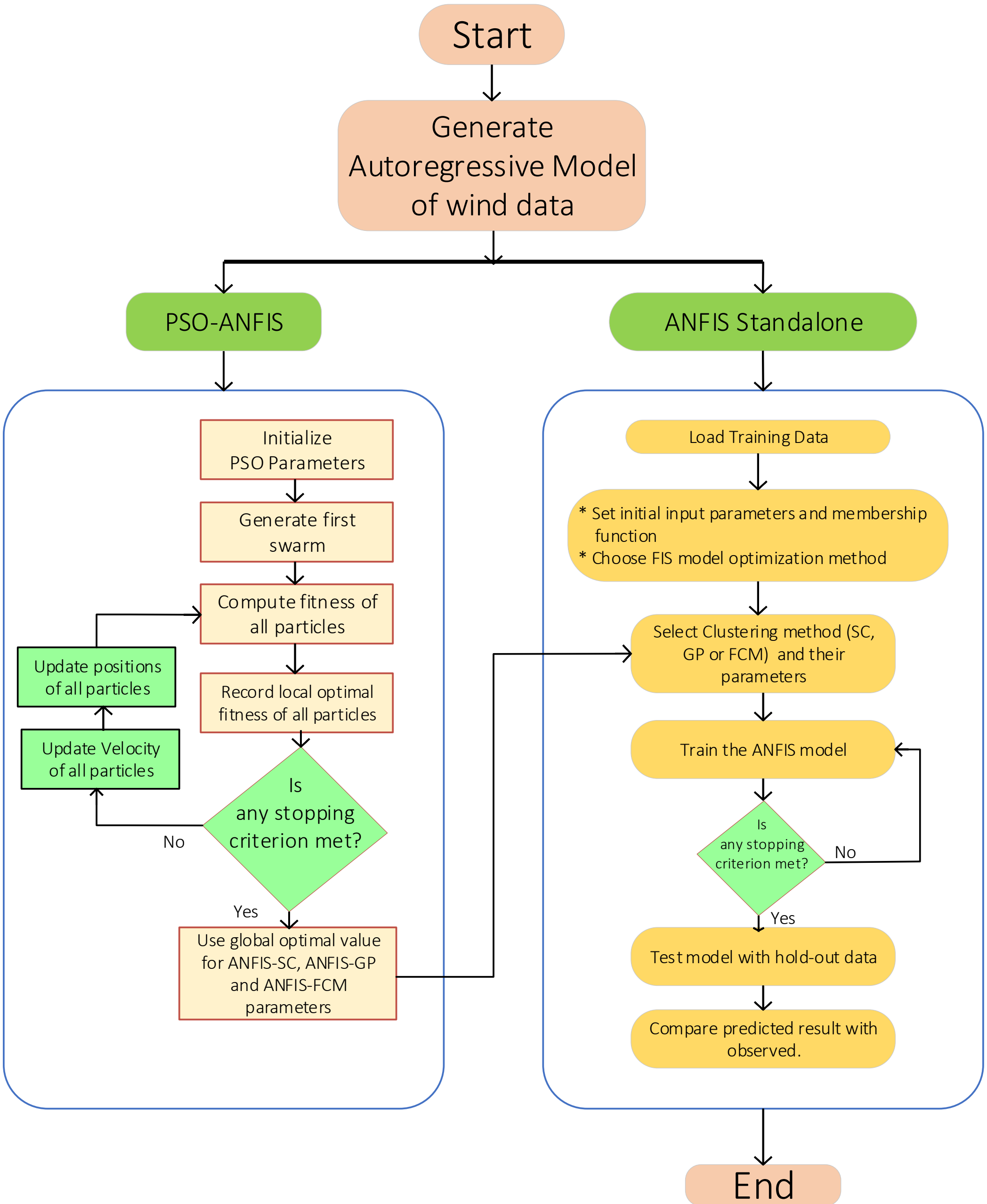

Figure 6. The flowchart of the standalone and hybrid ANFIS model.

3. Results and Discussions

The ANFIS program was computed with MATLAB (R2015a) installed on a desktop computer workstation with configuration 64 bits, 32GB RAM Intel (R) Core (TM) i7 5960X. This was to ensure lesser computational time because some clustering techniques like grid partitioning can be computationally intensive. As previously stated, 70% of the data was used for training while 30% of the data was used at the model testing phase for both standalone and hybrid models.

3.1 ANFIS Standalone

Figure 7-9 show comparison plots between the observed power output of the utility scale wind turbine and the forecast produced by standalone ANFIS models clustered with GP, SC and FCM respectively. It is observed that a strong agreement exists between the observed and the predicted power output for the three models. Each plot demonstrates variability associated with the wind resource which the predicted values closely approximates. Over-predictions and under-predictions occurred more with the GP-clustered model as shown in Figure 7 compared to the SC and FCM-clustered models as there are more over-predicted data points. Similarly, the FCM-clustered model also exhibits overprediction which is significant compared to the SC-based model. These overpredictions and underpredictions are due to underestimation or overestimation of the ANFIS model control parameters (Olatunji et al., 2019b).

Among the three standalone models, the SC-clustered model provides the most satisfactory agreement between the observed and the predicted power output with least miss-predictions.

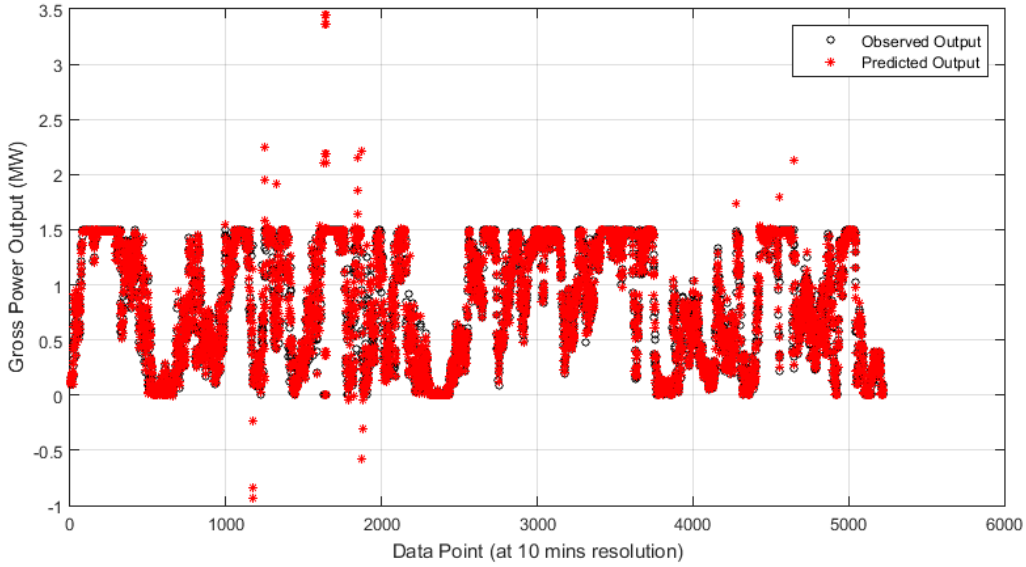

Figure 7. Test results of ANFIS-GP model with new observations compared with the predicted results

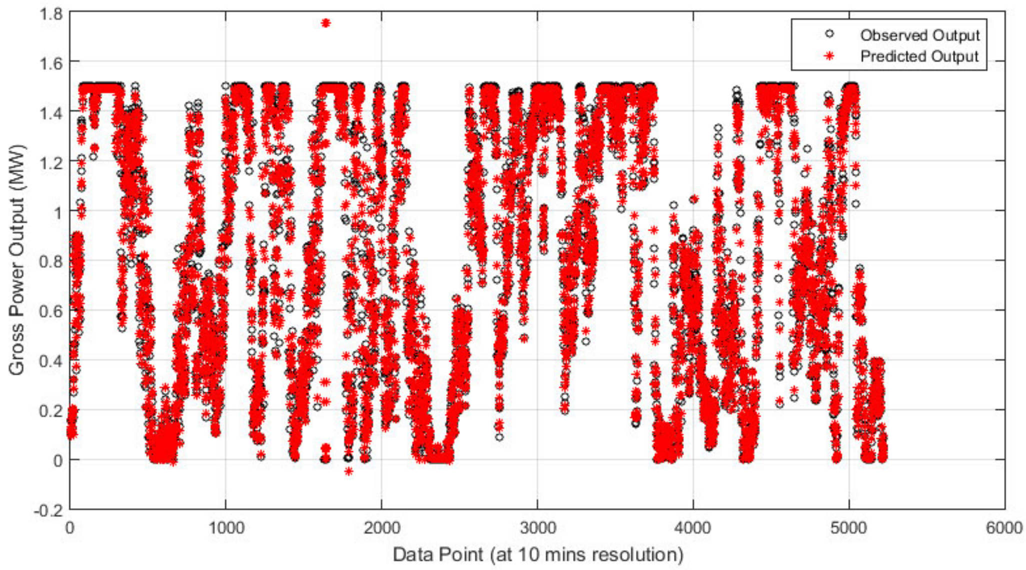

Figure 8. Plot of ANFIS-SC model with new observations compared with the predicted results

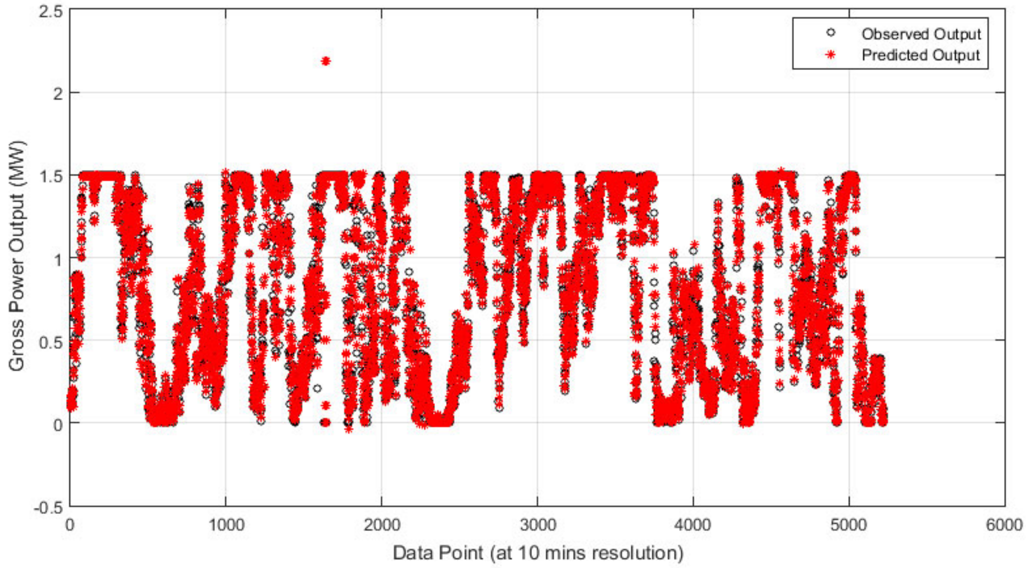

Figure 9. Test plot for ANFIS-FCM model with new observations compared with the predicted results.

3.2. Hybrid ANFIS Result

ANFIS hybridized with PSO for each of the three clustering techniques was experimented. The forecast using 30 % of the observed data was used for the PSO-ANFIS-GP, PSO-ANFIS-SC, and PSO-ANFIS-FCM. To ensure a basis for comparison with the ANFIS standalone models, the same testing data was used for the hybrid ANFIS model. Shown in Figure 10 is the plot of the observed and the predicted gross energy output for GP-clustered model with data resolution being 10 minutes. The GP clustering technique performed poorly on the data in the hybrid ANFIS compared with the standalone ANFIS model. Many datapoints were underpredicted, thus affecting the model accuracy. Several runs were performed with different parameters, however, same trend of prediction existed, thus, emphasising the preference of standalone GP-clustered model over its hybrid. The GP clustering technique is often associated with a large rule-base when used on a high-dimensional problem like this study. This increases the model complexity and could lead to curse of dimensionality. This performance shows that the optimization technique was not able to achieve global optimal values for the model parameters to achieve a finer grid structure on which the model performance largely depends.

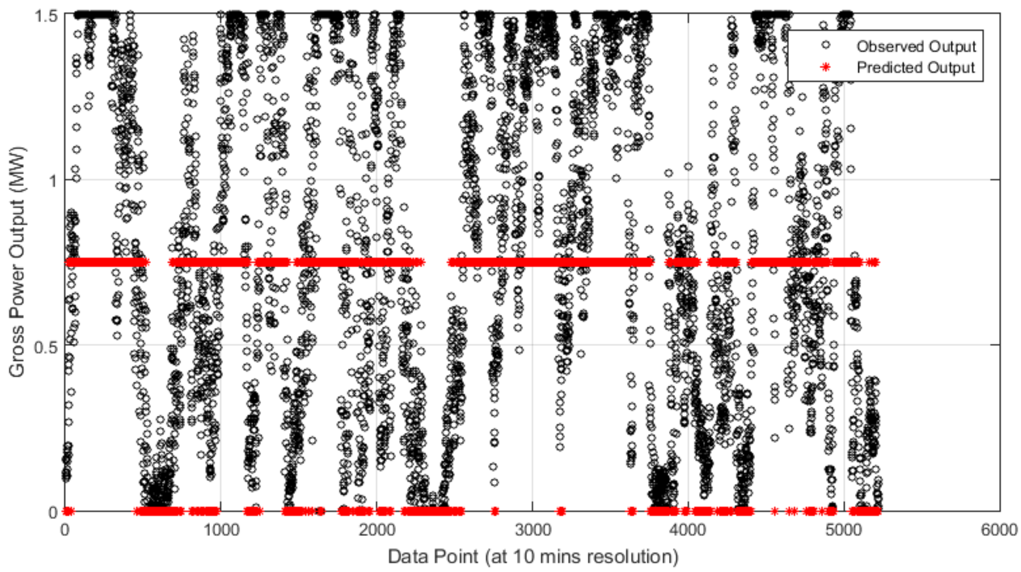

Figure 10. Plot of PSO-ANFIS-GP model with new observations compared with the predicted results

Shown in Figure 11-12 is the plot of the hybrid SC and FCM-clustered ANFIS model respectively. A strong agreement between the observed and the predicted power output is observed with less underpredictions and over predictions. The SC clustering technique (Figure 11), however, performs better than the FCM and GP in the hybrid ANFIS model with less variation between the observed and the predicted values. Similar agreement between the observed and predicted power output is observed in the FCM-clustered model as shown in Figure 12 except for its more mis-predictions. Asides visual observation of the predicted against the actual gross power, a statistical measure of accuracy of the model was performed and presented in Table 6.

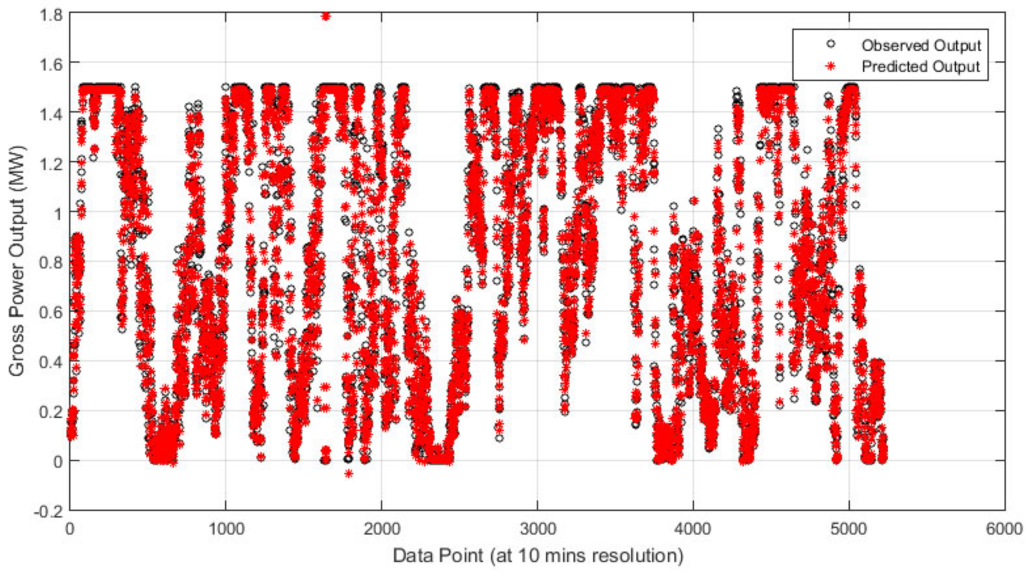

Figure 11. Plot of PSO-ANFIS-SC model with new observations compared with the predicted results

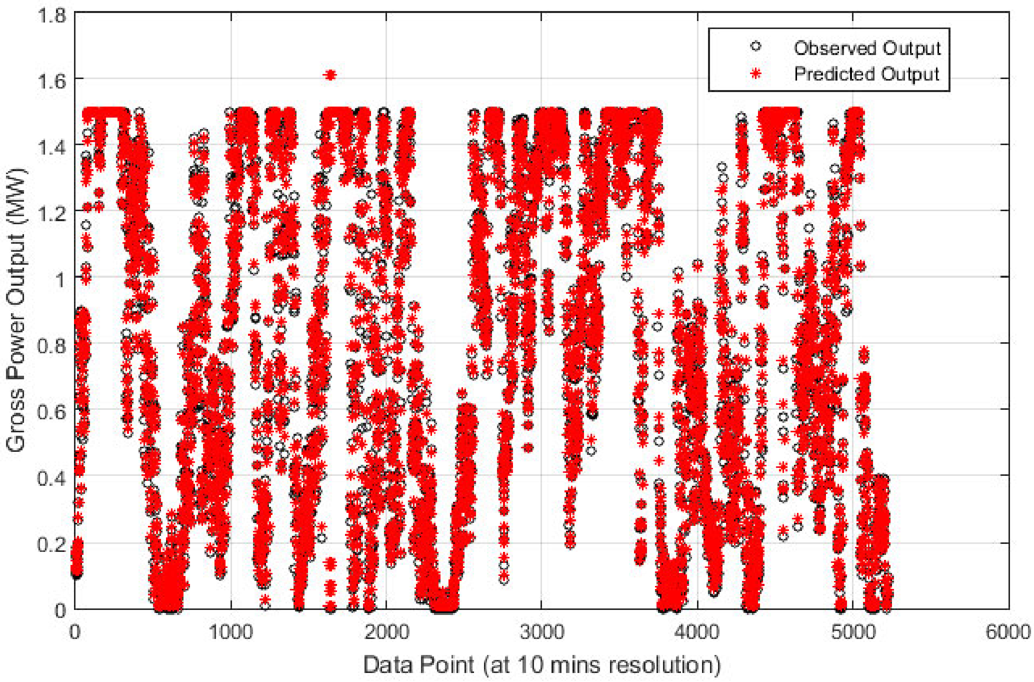

Figure 12. Plot of PSO-ANFIS-FCM model with new observations compared with the predicted results

3.1 Model evaluation

The model was tested for reliability and capability by performing error analysis on the hold-out data set (30 % of the observation data) used for new prediction. Common statistical metrics for model reliability measures were performed on the test data. These include the root mean square error (RMSE), mean absolute deviation (MAD), mean absolute percentage error (MAPE) and the relative mean bias error (rMBE) were used as performance metrics. As a measure of capability of the models, the relative mean bias error (rMBE) was introduced. This performance metric evaluates the reliability of the model. The closer its value is to zero, the more reliable the model is (Eminoglu and Turksoy, 2019) and a negative value signifies model capability to underestimate (Kwon et al., 2019). These were calculated as follows:

Root Mean square Error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N}[y_k - \widehat{y_k}]^2}{N}} \tag{21}$$

Mean Absolute Deviation (MAD):

$$MAD = \frac{1}{N}\sum_{k=1}^{N}|y_k - \bar{y}| \tag{22}$$

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{y_k - \widehat{y_k}}{y_k}\right| \times 100\% \tag{23}$$

relative Mean Bias Error (rMBE):

$$rMBE = \frac{1}{N}\sum_{k=1}^{N}\left(\frac{\widehat{y_k} - y_k}{y_k}\right) \tag{24}$$

Variance accounted for (VAF):

$$VAF = 1 - \left[\frac{var(\widehat{y_k} - y_k)}{var(y_k)}\right] \times 100 \tag{25}$$

Table 6 presents the performance evaluation results obtained for the three clustering techniques and their hybrid models at testing phase.

Table 6. Performance evaluation of models at the testing phase using new observations

	Standalone Models			Hybrid Models		
Metrics	ANFIS-SC	ANFIS-GP	ANFIS-FCM	PSO-ANFIS-SC	PSO-ANFIS-GP	PSO-ANFIS-FCM
MAD	0.077	0.085	0.078	0.078	0.375	0.079
MAPE	30.940	33.160	48.190	28.110	54.570	35.000
RMSE	0.132	0.189	0.139	0.127	0.461	0.137
VAF	94.307	89.410	93.630	94.311	51.581	94.332
rMBE	0.190	0.250	0.220	0.190	-0.063	0.250
CT (*secs*)	30.23	385.06	77.25	47.21	256.06	355.84

3.1.1. Statistical Performance Metrics

From Table 6, MAD, MAPE, RMSE, VAF, and rMBE were used as statistical performance measures for the standalone and hybrid models to clearly evaluate the model performance. While the MAD and RMSE measures the magnitude of the average error of prediction and the eligibility of the model for prediction (Olatunji et al., 2019a), the MAPE measures the models' forecast accuracy/goodness of fit. Closeness of the value of these metrics to zero is more preferred. However, to account for the asymmetric nature of the MAPE, the VAF metric was introduced to account for the actual variance between the observed power output and the predicted that is explained by the model. A value close to 100% is highly preferred.

In the standalone models, ANFIS clustered with SC technique offered the best results with a lowest MAD and RMSE values of 0.077 and 0.132 respectively (Table 6), though these values are just slightly lower compared to the results obtained from the FCM clustered model. Hence, the average error of the prediction is lesser in the SC-clustered standalone model compared to the FCM and GP-clustered models. Similarly, the MAPE results obtained from the SC-clustered model is lower compared to that obtained from the FCM and GP-clustered models. However, despite the high values of RMSE and MAD values obtained from the GP model ($RMSE = 0.189; MAD = 0.085$), its MAPE value is lesser than the FCM-clustered model $i.e. MAPE_{ANFIS-GP}(33.16) < MAPE_{ANFIS-FCM}(48.19)$. Hence by implication the GP-based model can be accurate in prediction, but the average error of the prediction can be higher than that of the FCM-based model. Comparing the reliability of the standalone models using their respective rMBE values, the SC-clustered model has the least rMBE value ($rMBE_{ANFIS-SC} = 0.19$) compared to the other two models. Although the prediction accuracy of the GP-clustered model is higher than the FCM-clustered model, the model offers a lesser reliability compared to the FCM-clustered model. From the values of the VAFs obtained for each model, the SC-clustered model is capable of accounting for 94.307% of the variance between the predicted and the observed gross power output of the models compared to the FCM and GP-based models with VAF values of 93.63 and 89.41% respectively. This further proves the effectiveness of the SC-clustered model.

Also, similar behaviour in the model performance was obtained in the hybrid models. From Table 6, the SC-clustered model has the least MAD and RMSE values of 0.078 and 0.127 respectively. However, a marginal difference exists between these values and that obtained from the FCM-clustered model, thus presenting FCM-based model as also effective with less prediction error. The hybrid SC-clustered model had the least MAPE value ($MAPE_{ANFIS-SC} = 28.11$) among the six models, thus emphasising the positive effects of clustering with SC technique and optimizing the model control parameters. Based on the values of VAFs obtained, the SC and FCM clustering techniques are capable of accounting for a high percentage of variance in the model compared to the GP-clustered model. From the rMBE values, the SC and FCM-clustered models offer high reliability, while the GP-clustered model has a high prospect for underestimation, hence unreliable in this study.

3.1.2. Computational time

Table 6 also presents the computational time of each of the six models as standalone and hybrid. It can be observed that the SC and FCM-clustered models requires lower computational time compared to the GP model. However, the computational time of the SC and FCM-clustered model increased by 16.98*secs* and 278.59*secs* respectively with model hybridization while an unexpected decrease was observed for GP-clustered model. Characteristic of the GP technique is the high reliance of its learning time on the grid definition process. A one-pass build-up of the grid definition process reduces the learning time as described by Joo and Chen, (2011), which consequentially reduces the model's computational time. This probably describes the reduction in computational time of the GP model when hybridized with PSO. However, this observation was only limited to the standalone ANFIS but not in the hybrid model. This could be due to optimization of one aspect of the curse of dimensionality associated with GP clustering and not others. Several aspects of curse of dimensionality exist in the GP clustering technique. These include scalability of the grid construction, noise and optimization of the density function across the data space towards selecting relevant attributes (Aggarwal and Reddy, 2013). The PSO function successfully achieved a one-pass build-up of the grid structure in the ANFIS model, however, a finer grid, which largely determines the model accuracy was not achieved. It is recommended that the grid-based partitioning of the input space be discarded in high-dimensional problems to minimise model complexity which could lead to overestimation or underestimation in the model (Nelles, 2001).

On the overall, FCM and SC are good clustering techniques, however, a comparison between the FCM-based ANFIS and the SC-based ANFIS models, at hybrid and standalone, shows that the SC-clustered model exceeds the FCM-based model in accuracy. Also, when computational time is to be minimized, the SC model is desirable since lesser time translate to lower cost of machine utilization. Similarly, parameter tuning of ANFIS model with PSO algorithm increases the prediction accuracy of the SC clustered ANFIS model, though at a higher computational time. The computational time, however, depends on several factors among which is the processor of the computing device which can vary from one computing device to another.

4 Conclusions

Renewable energy is fast replacing the fossil fuels with wind and solar energy harvesting increasing in dominance on a global scale. The wind energy is much preferred due to its higher capacity factor compared to the solar energy, though at a higher initial investment cost, which gives credence is given to resource forecasting. This study compares three data clustering techniques (SC, FCM, and GP techniques) in ANFIS modeling of short-term forecasting of the gross wind power output of a utility-scale wind turbine proposed to be deployed to Rhodes, Eastern Cape, South Africa. These clustering techniques were considered in standalone ANFIS and ANFIS tuned with PSO in an autoregressive manner. From our findings, SC and FCM clustering techniques could be effective, though computational time could be a trade-off. Both models are reliable for the wind power forecast as observed from their rMBE values. However, the SC clustering technique performed best on both standalone and optimized ANFIS models compared to the FCM and GP clustering technique. The SC-based ANFIS models recorded the lowest RMSE, MAD, and MAPE values, though the variations between these performance indices at its standalone and hybrid models are not very significant. The closeness of the predicted test data to the observed power output showed the potential of PSO-ANFIS-SC model as an effective predictive model in wind energy studies. However, model parameter underestimation occurred in the hybrid GP-based model which lead to a low prediction accuracy of the model.

The SC clustered ANFIS model performed best among the three clustering techniques considered either as standalone or hybrid. This validates its recommendation in the literature (Casalino et al., 2014; Chang et al., 2014; Chang and Chang, 2006) for data clustering. The accuracy of the SC-clustered model is hinged on an optimal selection of the radius of influence. Parameter tuning of ANFIS model with PSO algorithm, however, increases the model accuracy though at the expense of the computational time, thus resulting into a higher machine utilization cost to be accounted for. However, the use of parallel computing in hybrid ANFIS models is recommended for further studies to reduce the computational time in hybrid ANFIS model.

References

Adedeji, P., Madushele, N., Akinlabi, S., 2018. Adaptive Neuro-fuzzy Inference System (ANFIS) for a multi-campus institution energy consumption forecast in South Africa, in: Proceedings of the International Conference on Industrial Engineering and Operations Management Washington DC, USA, September 27-29, 2018.

Adedeji, Paul A., Akinlabi, S., Ajayi, O., Madushele, N., 2019. Non-linear autoregressive neural network (NARNET) with SSA filtering for a university enegy consumption forecast, in: 16th Global Conference on Sustainable Manufacturing- Sustainable Manufacturing for Global Circular Economy. pp. 176–183. https://doi.org/.1037//0033-2909.I26.1.78

Adedeji, P.A., Masebinu, S.O., Akinlabi, S.A., Madushele, N., 2019. Adaptive Neuro-fuzzy Inference System (ANFIS) in Energy System and Water Resources, in: Kumar, K., Davim, J.P. (Eds.), Optimization Using Evolutionary Algorithms and Metaheuristics: Applications in Engineering. CRC Press, Boca Raton, pp. 117–133.

Aggarwal, C.C., Reddy, C.K., 2013. DATA Custering Algorithms and Applications, Taylor & Francis Group.

Andrews, J.L., McNicholas, P.D., 2013. Using evolutionary algorithms for model-based clustering. Pattern Recognit. Lett. 34, 987–992. https://doi.org/10.1016/j.patrec.2013.02.008

Awan, J.A., Bae, D.H., 2014. Improving ANFIS Based Model for Long-term Dam Inflow Prediction by Incorporating Monthly Rainfall Forecasts. Water Resour. Manag. 28, 1185–1199. https://doi.org/10.1007/s11269-014-0512-7

Ayodele, T.R., Ogunjuyigbe, A.S.O., 2016. Wind energy potential of Vesleskarvet and the feasibility of meeting the South African ' s SANAE IV energy demand. Renew. Sustain. Energy Rev. 56, 226–234. https://doi.org/10.1016/j.rser.2015.11.053

Baker, L., Newell, P., Phillips, J., 2014. The Political Economy of Energy Transitions: The Case of South Africa. New Polit. Econ. 19, 791–818.

Barak, S., Sadegh, S.S., 2016. Forecasting energy consumption using ensemble ARIMA-ANFIS hybrid algorithm. Int. J. Electr. Power Energy Syst. 82, 92–104. https://doi.org/10.1016/j.ijepes.2016.03.012

Barati-Harooni, A., Najafi-Marghmaleki, A., Mohammadi, A.H., 2016. ANFIS modeling of ionic liquids densities. J. Mol. Liq. 224, 965–975. https://doi.org/10.1016/j.molliq.2016.10.050

Box, G.E., Jenkins, G.M., Reinsel, G.C., 2013. Time Series Analysis: Forecasting and Control. Wiley, New Jersey.

Çakit, E., Karwowski, W., 2015. Fuzzy inference modeling with the help of fuzzy clustering for predicting the occurrence of adverse events in an active theater of war. Appl. Artif. Intell. 29, 945–961.

Cape-ducluzeau, L., van der Westhuizen, C., 2015. Strategic Environmental Assessment for Renewable Energy in South Africa - Renewable Energy Development Zones (REDZs), in: 35th Annual Conference of the International Association for Impact Assessment.

Casalino, G., Del, N., Mencar, C., 2014. Subtractive clustering for seeding non-negative matrix factorizations. Inf. Sci. (Ny). 257, 369–387. https://doi.org/10.1016/j.ins.2013.05.038

Chahkoutahi, F., Khashei, M., 2017. A seasonal direct optimal hybrid model of computational intelligence and soft computing techniques for electricity load forecasting. Energy 140, 988–1004. https://doi.org/10.1016/j.energy.2017.09.009

Chang, F.J., Chang, Y.T., 2006. Adaptive neuro-fuzzy inference system for prediction of water level in reservoir. Adv. Water Resour. 29, 1–10. https://doi.org/10.1016/j.advwatres.2005.04.015

Chang, F.J., Chung, C.H., Chen, P.A., Liu, C.W., Coynel, A., Vachaud, G., 2014. Assessment of arsenic concentration in stream water using neuro fuzzy networks with factor analysis. Sci. Total Environ. 494–495, 202–210. https://doi.org/10.1016/j.scitotenv.2014.06.133

Chang, G.W., Lu, H.J., Chang, Y.R., Lee, Y.D., 2017. An improved neural network-based approach for short-term wind speed and power forecast. Renew. Energy 105, 301–311. https://doi.org/10.1016/j.renene.2016.12.071

Csereklyei, Z., Thurner, P.W., Langer, J., Küchenhoff, H., 2017. Energy paths in the European Union: A model-based clustering approach. Energy Econ. 65, 442–457. https://doi.org/10.1016/j.eneco.2017.05.014

de Oliveira, J.F.L., Ludermir, T.B., 2016. A hybrid evolutionary decomposition system for time series forecasting. Neurocomputing 180, 27–34. https://doi.org/10.1016/j.neucom.2015.07.113

Demirli, K., Cheng, S.X., Muthukumaran, P., 2003. Subtractive clustering based modeling of job sequencing with parametric search. Fuzzy Sets Syst. 137, 235–270. https://doi.org/10.1016/S0165-0114(02)00364-0

Dhanachandra, N., Manglem, K., Chanu, Y.J., 2015. Image Segmentation using K -means Clustering Algorithm and Subtractive Clustering Algorithm. Procedia - Procedia Comput. Sci. 54, 764–771. https://doi.org/10.1016/j.procs.2015.06.090

Dinda, P.A., O'Hallaron., D.R., 2000. Host load prediction using linear models. Cluster Comput. 3, 265–280.

Dong, F., Shi, L., 2019. Regional differences study of renewable energy performance : A case of wind power in China. J. Clean. Prod. 233, 490–500. https://doi.org/10.1016/j.jclepro.2019.06.098

Dunmade, I., Madushele, N., Adedeji, P.A., Akinlabi, E.T., 2019. A streamlined life cycle assessment of a coal-fired power plant: the South African case study. Environ. Sci. Pollut. Res. https://doi.org/10.1007/s11356-019-05227-6

Eberhart, R., Kennedy, J., 2002. A new optimizer using particle swarm theory, in: Sixth International Symposium on Micro Machine and Human Science. pp. 39–43. https://doi.org/10.1109/mhs.1995.494215

Eminoglu, U., Turksoy, O., 2019. Power curve modeling for wind turbine systems: a comparison study. Int. J. Ambient Energy 1–10. https://doi.org/10.1080/01430750.2019.1630302

Endo, H.Ã., Randall, R.B., 2007. Enhancement of autoregressive model based gear tooth fault detection technique by the use of minimum entropy deconvolution filter. Mech. Syst. Signal Process. 21, 906–919. https://doi.org/10.1016/j.ymssp.2006.02.005

Engelbrecht, A.P., Cleghorn, C.W., Engelbrecht, A., 2019. Recent advances in particle swarm optimization analysis and understanding, in: GECCO '19: Proceedings of the Genetic and Evolutionary Computation Conference Companion. pp. 1–28. https://doi.org/10.1145/3319619.3323368

Erenoğlu, A.K., Erdinç, O., Taşcıkaraoğlu, A., 2019. History of Electricity, in: Pathways to a Smarter Power System. pp. 1–27. https://doi.org/10.1016/B978-0-08-102592-5.00001-6

Ester, M., Kriegel, H.-P., Jorg, S., Xu, X., 1996. A Density-Based Clustering Algorithms for Discovering Clusters in Large Spatial Databases with Noise, in: KDD-96 Proceedings. pp. 226–231. https://doi.org/10.1016/B978-044452701-1.00067-3

Fattahi, H., 2016. Adaptive Neuro Fuzzy Inference System Based on Fuzzy C–Means Clustering Algorithm, a Technique for Estimation of Tbm Penetration Rate. Int. J. Optim. Civ. Eng. 6, 159–171.

Galindo, J., 2008. Handbook of Research on Fuzzy Information Processing in Databases. Information Science Reference, IGI Global, Hershey, New York, USA.

Ghasemaghaei, M., Calic, G., 2019. Can big data improve firm decision quality? The role of data quality and data diagnosticity. Decis. Support Syst. 120, 38–49. https://doi.org/10.1016/J.DSS.2019.03.008

Ghasemaghaei, M., Ebrahimi, S., Hassanein, K., 2018. Data analytics competency for improving firm decision making performance. J. Strateg. Inf. Syst. 27, 101–113.

Gogoi, R., Sarma, K.K., 2012. ANFIS based Information Extraction using K-means Clustering for Application in Satellite Images. Int. J. Comput. Appl. 50, 13–18. https://doi.org/10.5120/7782-0872

Grün, B., 2016. Model-Based Clustering, in: Celeux, G., Frühwirth-Schnatter, S., Christian, P.R.

(Eds.), Handbook of Mixture Analysis. pp. 331–373. https://doi.org/10.1007/s00357-016-9211-9
Hagh, M.T., Khalili, T., 2019. A review of fault ride through of PV and wind renewable energies in grid codes. Int. J. Energy Res. 43, 1342–1356. https://doi.org/10.1002/er.4247
Hernández-Escobedo, Q., Saldaña-Flores, R., Rodríguez-García, E.R., Manzano-Agugliaro, F., 2014. Wind energy resource in Northern Mexico. Renew. Sustain. Energy Rev. 32, 890–914. https://doi.org/10.1016/j.rser.2014.01.043
Hernández, L., Baladrón, C., Aguiar, J.M., Carro, B., Sánchez-Esguevillas, A., 2012. Classification and clustering of electricity demand patterns in industrial parks. Energies 5, 5215–5228. https://doi.org/10.3390/en5125215
Hillier, F.S., 2001. Principles of Forecasting: A Handbook for researchers and practitioners. https://doi.org/10.1007/978-0-306-47630-3
Horita, F.E., Albuquerque, J.P. de, Marchezini, V., Mendiondo, E.M., 2017. Bridging the gap between decision-making and emerging big data sources: an application of a model-based framework to disaster management in Brazil. Decis. Support Syst. 97, 12–22.
Jang, J.S.R., 1993. ANFIS: adaptive-network-based fuzzy inference system. IEEE Trans. Syst. Man. Cybern. 23, 665–685. https://doi.org/10.1109/21.256541
Joo, Y.H., Chen, G., 2011. Fuzzy Systems Modeling: An Introduction, in: Encyclopedia of Artificial Intelligence. pp. 734–743.
Karaboga, D., Kaya, E., 2018. Adaptive network based fuzzy inference system (ANFIS) training approaches: a comprehensive survey. Artif. Intell. Rev. 1–31. https://doi.org/10.1007/s10462-017-9610-2
Kassa, Y., Zhang, J.H., Zheng, D.H., Wei, D., 2017. Short term wind power prediction using ANFIS, in: 2016 IEEE International Conference on Power and Renewable Energy, ICPRE 2016. IEEE, pp. 388–393. https://doi.org/10.1109/ICPRE.2016.7871238
Keeley, A.R., Ikeda, Y., 2017. Determinants of foreign direct investment in wind energy in developing countries. J. Clean. Prod. 161, 1451–1458. https://doi.org/10.1016/j.jclepro.2017.05.106
Kennedy, J., 1998. The Behaviour of Particles, in: Porto, V.W., Saravanan, N., Waagen, D., Eiben, A.E. (Eds.), Evolutionary Programming VII: Proceedings of 7th Annual Conference of Evolutionary Programming Conf. San Diego. Springer-Verlag, pp. 581–589.
Khalili, T., Jafari, A., Abapour, M., Mohammadi-Ivatloo, B., 2019. Optimal battery technology selection and incentive-based demand response program utilization for reliability improvement of an insular microgrid. Energy 169, 92–104. https://doi.org/10.1016/j.energy.2018.12.024
Khosravi, A., Nunes, R.O., Assad, M.E.H., Machado, L., 2018. Comparison of artificial intelligence methods in estimation of daily global solar radiation. J. Clean. Prod. 194, 342–358. https://doi.org/10.1016/j.jclepro.2018.05.147
Küçükdeniz, T., Baray, A., Ecerkale, K., 2012. Expert Systems with Applications Integrated use of fuzzy c-means and convex programming for capacitated multi-facility location problem 39, 4306–4314. https://doi.org/10.1016/j.eswa.2011.09.102
Kuwil, F.H., Shaar, F., T, Ercan Topcu, A., Murtagh, F., 2014. A New Data Clustering Algorithm Based on Critical Distance Methodology. Expert Syst. Appl. https://doi.org/10.1016/j.eswa.2019.03.051
Kwon, Y., Kwasinski, Alexis, Kwasinski, Andres, 2019. Solar Irradiance Forecast Using Naïve Bayes Classifier Based on Publicly Available Weather Forecasting Variables. Energies 12, 1–13.
Lahouar, A., Hadj, J. Ben, 2017. Hour-ahead wind power forecast based on random forests. Renew. Energy 109, 529–541. https://doi.org/10.1016/j.renene.2017.03.064
Lee, S., Kim, H., Son, E., Lee, S., 2012. Effects of design parameters on aerodynamic performance of a counter-rotating wind turbine. Renew. Energy 140, 44–42.
Liu, F., Sun, F., Liu, W., Wang, T., Wang, H., Wang, X., Lim, W.H., 2019. On wind speed pattern and energy potential in China. Appl. Energy 236, 867–876. https://doi.org/10.1016/j.apenergy.2018.12.056
Mathew, S., 2006. Wind Energy: Fundamentals, Resource Analysis and Economics. Springer-Verlag Berlin Heidelberg, Netherlands.
McEwan, C., 2017. Spatial processes and politics of renewable energy transition: Land, zones and frictions in South Africa. Polit. Geogr. 56, 1–12. https://doi.org/10.1016/j.polgeo.2016.10.001

Melnykov, V., Zhu, X., 2018. On model-based clustering of skewed matrix data. J. Multivar. Anal. 167, 181–194. https://doi.org/10.1016/j.jmva.2018.04.007
Millonas, M., 1994. Swarms, phase transitions, and collective intelligence. Artificial Lue Ill, Addison Wesley, Reading, MA.
Moreno, S.R., dos Santos Coelho, L., 2018. Wind speed forecasting approach based on Singular Spectrum Analysis and Adaptive Neuro Fuzzy Inference System. Renew. Energy 126, 736–754. https://doi.org/10.1016/j.renene.2017.11.089
Murthy, K.S.R., Rahi, O.P., 2017. A comprehensive review of wind resource assessment. Renew. Sustain. Energy Rev. 72, 1320–1342. https://doi.org/10.1016/j.rser.2016.10.038
Najib, M., Salleh, M., Hussain, K., 2016. A Review of Training Methods of ANFIS for Applications in Business and Economics. Int. J. Univ. Tun Hussein Serv. Sci. Technol. 9, 165–172.
Narayanan, S.J., Paramasivam, I., Bhatt, R.B., Khalid, M., 2015. A Study on the Approximation of Clustered Data to Parameterized Family of Fuzzy Membership Functions for the Induction of Fuzzy Decision Trees 15, 75–96. https://doi.org/10.1515/cait-2015-0030
Nayak, G.K., Narayanan, S.J., Paramasivam, I., 2013. Development and Comparative Analysis Of Fuzzy Inference Systems for Predicting Customer Buying Behavior 5, 4093–4108.
Nehrenheim, E., 2018. Energy and Natural Resources. Encycl. Anthr. https://doi.org/10.1016/B978-0-12-809665-9.05353-2
Nelles, O., 2001. Nonlinear system identification: from classical approaches to neural Networks and Fuzzy Models, Book. Springer-Verlag Berlin Heidelberg. https://doi.org/10.1007/978-3-662-04323-3
Nourani, V., Partoviyan, A., 2018. Hybrid denoising-jittering data pre-processing approach to enhance multi-step-ahead rainfall–runoff modeling. Stoch. Environ. Res. Risk Assess. 32, 545–562. https://doi.org/10.1007/s00477-017-1400-5
Olatunji, O., Akinlabi, S., Madushele, N., Adedeji, P.A., 2019a. Estimation of Municipal Solid Waste (MSW) combustion enthalpy for energy recovery. EAI Endorsed Trans. Energy Web 6.
Olatunji, O., Akinlabi, S., Nkosinathi, M., Adedeji, P.A., 2019b. Estimation of the Elemental Composition of Biomass Using Hybrid Adaptive Neuro-Fuzzy Inference System. Bioenergy Res. 12, 642–652.
Pan, W.T., 2009. Forecasting classification of operating performance of enterprises by zscore combining ANFIS and genetic algorithm. Neural Comput. Appl. 18, 1005–1011. https://doi.org/10.1007/s00521-009-0243-5
Pelacchi, P., Poli, D., 2010. The influence of wind generation on power system reliability and the possible use of hydrogen storages. Electr. Power Syst. Res. 80, 249–255. https://doi.org/10.1016/j.epsr.2009.09.007
Pousinho, H.M.I., Mendes, V.M.F., Catalão, J.P.S., 2011. A hybrid pso-anfis approach for short-term wind power prediction in Portugal. Energy Convers. Manag. 52, 397–402. https://doi.org/10.1016/j.enconman.2010.07.015
Pramanik, N., Panda, R.K., 2009. Application of neural network and adaptive neuro-fuzzy inference systems for river flow prediction. Hydrol. Sci. J. 54, 247–260. https://doi.org/10.1623/hysj.54.2.247
Ramón, J., Dopico, R., 2011. Encyclopedia of Artificial Intelligence, Encyclopedia of Artificial Intelligence. Information Science Reference, IGI Global, Hershey, New York, USA. https://doi.org/10.4018/978-1-59904-849-9
Rezaei, M., Zarandi, M.H.F., 2011. Facility location via fuzzy modeling and simulation. Appl. Soft Comput. 11, 5330–5340.
Rezakazemi, M., Dashti, A., Asghari, M., Shirazian, S., 2017. H2-selective mixed matrix membranes modeling using ANFIS, PSO-ANFIS, GA-ANFIS. Int. J. Hydrogen Energy 42, 15211–15225. https://doi.org/10.1016/j.ijhydene.2017.04.044
Ross, T.J., 2004. Fuzzy Logic with Engineering Applications, Wiley. https://doi.org/10.1002/9781119994374
Sammaknejad, N., Zhao, Y., Huang, B., 2019. A review of the Expectation Maximization algorithm in data-driven process identification. J. Process Control 73, 123–136. https://doi.org/10.1016/j.jprocont.2018.12.010
SANEDI, 2016. Delivering Sustainable Energy Access.

Sassi Hidri, M., Zoghlami, M.A., Ben Ayed, R., 2018. Speeding up the large-scale consensus fuzzy clustering for handling Big Data. Fuzzy Sets Syst. 348, 50–74. https://doi.org/10.1016/j.fss.2017.11.003
Semero, Y.K., Zheng, D., Zhang, J., 2018. A PSO-ANFIS based Hybrid Approach for Short Term PV Power Prediction in Microgrids. Electr. Power Components Syst. 46, 1–9. https://doi.org/10.1080/15325008.2018.1433733
Shabaan, S., Abu El-Sebah, M.I., Bekhit, P., 2018. Maximum power point tracking for photovoltaic solar pump based on ANFIS tuning system. J. Electr. Syst. Inf. Technol. 5, 11–22. https://doi.org/10.1016/j.jesit.2018.02.002
Shamshirband, S., Ćojbašić, Ž., Yee, P.L., Al-Shammari, E.T., Petković, D., Zalnezhad, E., Taher, R.S., 2016. Comparative study of clustering methods for wake effect analysis in wind farm. Energy 95, 573–579. https://doi.org/10.1016/j.energy.2015.11.064
Sheikh, R., Raghuwanshi, M., Jaiswal, A., 2008. Genetic algorithm based clustering: a survey, in: First International Conference on Emerging Trends in Engineering and Technology, ICETET ’08.
Shihabudheen, K. V, Pillai, G.N., 2018. Knowle dge-Base d Systems Recent advances in neuro-fuzzy system : A survey. Knowledge-Based Syst. 0, 1–27. https://doi.org/10.1016/j.knosys.2018.04.014
Shoaib, M., Siddiqui, I., Rehman, S., Khan, S., Alhems, L.M., 2019. Assessment of wind energy potential using wind energy conversion system. J. Clean. Prod. 216, 346–360. https://doi.org/10.1016/j.jclepro.2019.01.128
Sørensen, P., Litong-palima, M., Hahman, A.N., Heunis, S., Ntusi, M., Hansen, J.C., 2018. Wind power variability and power system reserves in South Africa. J. Energy 29, 59–71. https://doi.org/10.17159/2413-3051/2017/v29i1a2067
Stathopoulos, T., Alrawashdeh, H., Al-quraan, A., Blocken, B., Dilimulati, A., Paraschivoiu, M., Pilay, P., 2018. Urban wind energy: Some views on potential and challenges. J. Wind Eng. Ind. Aerodyn. 179, 146–157. https://doi.org/10.1016/j.jweia.2018.05.018
Stefanakos, C., 2016. Fuzzy time series forecasting of nonstationary wind and wave data. Ocean Eng. 121, 1–12. https://doi.org/10.1016/j.oceaneng.2016.05.018
Suparta, W., Alhasa, K.M., 2016. Adaptive Neuro-fuzzy Inference System, in: Modeling of Tropospheric Delays Using ANFIS. pp. 5–19. https://doi.org/10.1007/978-3-319-28437-8
Tang, R., Fong, S., 2018. Clustering big IoT data by metaheuristic optimized mini-batch and parallel partition-based DGC in Hadoop. Futur. Gener. Comput. Syst. 86, 1395–1412. https://doi.org/10.1016/j.future.2018.03.006
Tien Bui, D., Pradhan, B., Lofman, O., Revhaug, I., Dick, O.B., 2012. Landslide susceptibility mapping at Hoa Binh province (Vietnam) using an adaptive neuro-fuzzy inference system and GIS. Comput. Geosci. 45, 199–211. https://doi.org/10.1016/j.cageo.2011.10.031
Torrecilla, J.L., Romo, J., 2018. Data learning from big data. Stat. Probab. Lett. 136, 15–19. https://doi.org/10.1016/j.spl.2018.02.038
Van der Linde, H.A., 1996. Wind Energy in south Africa. Renew. energy 9, 880–883.
Vasileva-Stojanovska, T., Vasileva, M., Malinovski, T., Trajkovik, V., 2015. An ANFIS model of quality of experience prediction in education. Appl. Soft Comput. J. 34, 129–138. https://doi.org/10.1016/j.asoc.2015.04.047
Verma, M., Srivastava, M., Chack, N., Diswar, A.K., Gupta, N., 2012. A Comparative Study of Various Clustering Algorithms in Data Mining. Int. J. Eng. Res. Appl. 2, 1379–1384.
Wang, Z., Zhang, Y., Fu, H., 2014. Autoregressive Prediction with Rolling Mechanism for Time Series Forecasting with Small Sample Size. Math. Probl. Eng. 2014, 1–9. https://doi.org/10.1155/2014/572173
Zare, M., Koch, M., 2018. Groundwater level fluctuations simulation and prediction by ANFIS- and hybrid Wavelet-ANFIS/Fuzzy C-Means (FCM) clustering models: Application to the Miandarband plain. J. Hydro-Environment Res. 18, 63–76. https://doi.org/10.1016/j.jher.2017.11.004
Zuo, L., Hou, L., Zhang, W., Geng, S., Wu, W., 2010. Application of PSO-adaptive neural-fuzzy inference system (ANFIS) in analog circuit fault diagnosis. Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics) 6146 LNCS, 51–57.

https://doi.org/10.1007/978-3-642-13498-2_7